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AN INTELLIGENT IOT-BASED IRRIGATION DECISION SYSTEM USING SENSOR FUSION AND LONG SHORT-TERM MEMORY NETWORKS

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ABSTRACT

Efficient water management is a critical challenge in modern agriculture due to increasing water scarcity and climate variability. This paper presents an intelligent IoT-based irrigation decision system that integrates multi-sensor data fusion with Long Short-Term Memory (LSTM) networks for real-time irrigation scheduling. Environmental data, including soil moisture, temperature, humidity, and solar radiation, are collected through distributed IoT sensor networks and processed using data fusion techniques to improve data reliability and completeness. The fused data is then utilized by an LSTM-based deep learning model to capture temporal dependencies and accurately predict soil moisture trends and crop water requirements.

The proposed system enables dynamic and adaptive irrigation decisions by considering real-time environmental variations, thereby replacing traditional threshold-based methods. Experimental analysis demonstrates that the LSTM-based approach significantly improves prediction accuracy and water-use efficiency compared to conventional machine learning models. Furthermore, the system supports scalable deployment and remote monitoring through cloud integration, making it suitable for precision agriculture applications. Overall, the proposed framework enhances sustainable water management, optimizes irrigation scheduling, and contributes to the development of intelligent agricultural systems.

KEYWORDS: IoT, Smart Irrigation, Sensor Fusion, LSTM, Soil Moisture Prediction, Precision Agriculture

1. Introduction

Agriculture is one of the largest consumers of freshwater resources, making efficient irrigation management essential in the presence of increasing water scarcity and climate variability. Traditional irrigation methods, such as manual scheduling and fixed time-based watering, often result in over-irrigation or under-irrigation, causing water wastage and reduced crop productivity [1][2]. With the advancement of the Internet of Things (IoT), smart irrigation systems have emerged that utilize environmental sensors to monitor soil moisture, temperature, and humidity in real time. These systems enable data-driven decision-making and improve water-use efficiency and crop yield [3][4].

Despite these advancements, existing IoT-based irrigation systems still face several technical challenges. Sensor data collected from agricultural environments is often noisy, incomplete, or inconsistent because of environmental disturbances and hardware limitations [5][6]. Furthermore, many conventional machine learning techniques are unable to effectively capture temporal dependencies in environmental and soil moisture data, which are critical for accurate irrigation scheduling. Recent studies have shown that deep learning models significantly improve prediction performance, yet there remains a need for robust systems capable of integrating multi-source sensor data and adapting to dynamic agricultural conditions [7][8][9].

To overcome these limitations, recent research has focused on combining data fusion techniques with advanced deep learning approaches. Sensor fusion methods integrate heterogeneous environmental data from multiple sources to improve reliability and reduce uncertainty in irrigation decision-making [10]. Deep learning architectures, particularly Long Short-Term Memory (LSTM) networks, have demonstrated strong capability in modeling long-term temporal dependencies in soil moisture and environmental datasets [11][12]. In addition, IoT-enabled cloud and edge computing platforms support real-time monitoring, scalable deployment, and intelligent irrigation control in precision agriculture environments [13][14].

The primary objective of this study is to develop an intelligent irrigation decision system that integrates IoT sensor networks, data fusion mechanisms, and LSTM-based deep learning models for real-time irrigation scheduling. The proposed framework aims to improve prediction accuracy, optimize water utilization, and provide adaptive decision-making under changing environmental conditions. By combining temporal modeling with multi-sensor data integration, the system addresses the limitations of traditional rule-based and standalone machine learning approaches [15][16].

The proposed solution employs distributed IoT sensors to continuously collect environmental data such as soil moisture, temperature, and humidity. The collected data is preprocessed and fused to generate reliable inputs for the LSTM prediction model. The model forecasts soil moisture trends and irrigation requirements, enabling automated and efficient water allocation. Compared with conventional irrigation systems, the proposed approach improves decision accuracy, minimizes resource wastage, and supports sustainable agricultural practices [17][18].

In summary, this paper presents a comprehensive framework for intelligent irrigation management by integrating IoT technologies, sensor fusion methods, and deep learning techniques. The proposed system contributes to the advancement of precision agriculture by addressing major challenges related to data reliability, temporal dependency modeling, and real-time irrigation decision-making, ultimately improving water-use efficiency and agricultural productivity [19][20].

2. Related Work

This section reviews recent research contributions in intelligent irrigation systems focusing on deep learning, IoT-enabled monitoring, and reinforcement learning techniques for precision agriculture.

2.1 Deep Learning-Based Irrigation Prediction

Deep learning approaches have been extensively applied for soil moisture estimation and irrigation prediction because of their capability to learn complex temporal and spatial patterns from sensor data. Kashyap et al. [2] proposed an IoT-assisted irrigation framework integrated with deep learning algorithms to automate irrigation scheduling and improve water-use efficiency. Adeyemi et al. [9] demonstrated that Long Short-Term Memory (LSTM) networks outperform conventional machine learning techniques in soil moisture forecasting due to their ability to capture long-term temporal dependencies. Fang et al. [10] combined Convolutional Neural Networks (CNN) with LSTM models to enhance evapotranspiration prediction accuracy. Similarly, Zhang et al. [11] utilized autoencoders for effective feature extraction and noise reduction in sensor datasets. Saikai et al. [6] further improved irrigation prediction performance by applying deep learning techniques to high-dimensional agricultural sensor data.

2.2 IoT-Based Smart Irrigation Systems

IoT-enabled smart irrigation systems integrate environmental sensors, wireless communication, cloud computing, and edge computing technologies for real-time monitoring and automated decision-making. Kingslin and Vaishnavi [1] presented a comprehensive survey of IoT-based irrigation architectures and communication frameworks used in precision agriculture. Anjum et al. [16] developed a cloud-assisted irrigation management system integrated with machine learning for automated irrigation control. García et al. [17] introduced edge-computing mechanisms to minimize latency and improve real-time responsiveness in irrigation systems. Elijah et al. [18] emphasized the importance of big data analytics in precision agriculture for efficient resource utilization and crop management. Jawad et al. [19] focused on wireless sensor networks and energy-efficient communication strategies for sustainable agricultural monitoring.

2.3 Reinforcement Learning-Based Irrigation Control

Reinforcement learning (RL) techniques have recently gained attention for adaptive and autonomous irrigation scheduling under dynamic environmental conditions. Saikai et al. [6] applied deep reinforcement learning for intelligent water allocation and adaptive irrigation management. Kelly et al. [12] optimized irrigation timing using RL-based strategies, resulting in improved long-term crop yield and water conservation. Li et al. [13] proposed a Q-learning-based irrigation framework suitable for low-resource agricultural environments. Shamshiri et al. [14] investigated AI-driven greenhouse irrigation systems using adaptive control mechanisms. Furthermore, Adeyemi et al. [15] compared deep learning and reinforcement learning approaches and concluded that RL models provide greater adaptability and decision-making capability in changing environmental conditions.

3. Working Architecture of the Intelligent IoT-Based Irrigation System

The working system is designed as a multi-layer architecture that integrates IoT sensor networks, data fusion, deep learning, and automated control to enable real-time irrigation decision-making. As shown in Figure 1, the architecture consists of the following layers:

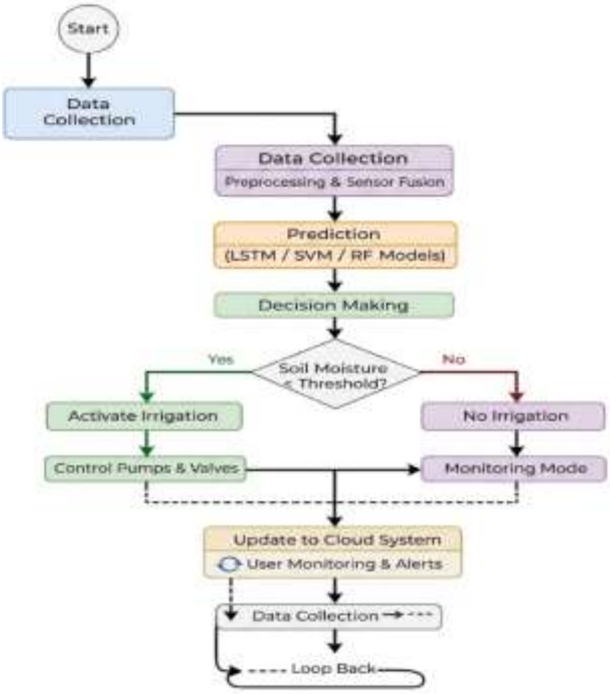

Figure 1: Architecture of the Intelligent IoT-Based Irrigation System

A. Data Acquisition Layer

This layer consists of distributed IoT sensors deployed across the agricultural field to continuously collect environmental data such as soil moisture, temperature, humidity, and solar radiation. These sensors provide real-time, multi-dimensional input required for intelligent irrigation decisions.

B. Data Preprocessing and Sensor Fusion Layer

The raw sensor data is often noisy and may contain missing or inconsistent values. In this layer, preprocessing techniques such as noise filtering, interpolation, and normalization are applied to improve data quality. Sensor fusion methods combine multiple sensor readings into a single reliable representation, enhancing data accuracy and consistency.

C. Prediction Layer

The processed and fused data is fed into a Long Short-Term Memory (LSTM) model, which captures temporal dependencies in environmental data. The model predicts future soil moisture levels and irrigation requirements by learning from historical patterns and real-time inputs. For comparative analysis, additional models such as Support Vector Machine (SVM) and Random Forest (RF) are also considered.

D. Decision-Making Layer

Based on the predicted soil moisture values, this layer determines whether irrigation is required and estimates the amount of water needed. A threshold-based decision rule combined with predictive outputs ensures adaptive and efficient irrigation scheduling.

E. Control and Actuation Layer

This layer executes the irrigation decisions by sending control signals to hardware components such as pumps, valves, and sprinklers. The system automatically activates or deactivates irrigation, enabling fully automated operation with minimal human intervention.

F. Cloud and User Interface Layer

All system data, including sensor readings, predictions, and irrigation actions, are stored and managed on a cloud platform. Users can monitor real-time conditions, receive alerts, and control the system through mobile or web-based interfaces, ensuring remote accessibility and scalability.

4. Result Analysis

The performance of the proposed intelligent IoT-based irrigation system is evaluated at each architectural layer to analyze its effectiveness in data processing, prediction, decision-making, and system automation.

The Data Acquisition Layer is responsible for collecting real-time environmental data using IoT sensors such as soil moisture, temperature, humidity, and solar radiation sensors. The performance of this layer is evaluated based on data completeness, accuracy, and consistency, which directly impact the overall system performance.

The quality of collected data is measured using the **completeness metric in** Equation (1):

$$\text{Completeness} = \frac{\text{Total Valid Records}}{\text{Total Records}} \times 100 \ (1)$$

Table 1. Data Acquisition Layer Performance Analysis

Parameter	**Total Records**	**Valid Records**	**Missing Records**	**Completeness (%)**
Soil Moisture	1000	942	58	94.2
Temperature	1000	955	45	95.5
Humidity	1000	948	52	94.8
Solar Radiation	1000	930	70	93.0

In Table 1, The Data Acquisition Layer shows high data reliability, with all parameters achieving over 93% completeness out of 1000 records. Temperature has the highest data availability, while solar radiation has slightly more missing values due to environmental factors. Overall, the dataset is sufficiently complete, ensuring effective preprocessing and accurate model predictions in later stages.

The Data Preprocessing and Sensor Fusion Layer enhances the quality and reliability of raw IoT sensor data before it is used for prediction. This layer removes noise, handles missing values, normalizes data, and combines multiple sensor readings to produce accurate and stable inputs.
The effectiveness of this layer is evaluated using the **error reduction metric Equation (2)**:

$$Error_{\text{reduction}} = \frac{E_{raw}-E_{\text{processed}}}{E_{raw}} \ (2)$$

Table 2: Preprocessing and Sensor Fusion Performance

Parameter	**Raw Error (E(raw))**	**Processed Error (E(processed))**	**Error Reduction (%)**
Soil Moisture	0.065	0.032	50.8
Temperature	0.048	0.025	47.9
Humidity	0.052	0.028	46.1
Solar Radiation	0.071	0.036	49.3

In table 2, the preprocessing and sensor fusion layer significantly reduces error across all parameters, achieving nearly **45–50% improvement**. This demonstrates its effectiveness in removing noise, handling missing values, and producing high-quality data for accurate prediction.

The output of the Data Preprocessing and Sensor Fusion Layer serves as the refined input for the Prediction Layer. The impact of this improved data quality is evaluated by comparing the prediction performance before and after preprocessing.
The prediction performance is measured using standard metrics Equation 3 and Equation 4:

$$\mathrm{MAE} = \frac{1}{n}\sum|y_i - \hat{y}_i| \quad (3)$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum(y_i - \hat{y}_i)^2} \quad (4)$$

Table 3: Comprehensive Prediction Performance Analysis

Model	**MAE (Raw)**	**MAE (Processed)**	**RMSE (Raw)**	**RMSE (Processed)**	**Accuracy (Raw %)**	**Accuracy (Processed %)**	**Improvement (%)**
LSTM (Proposed)	0.045	0.021	0.067	0.034	86.5	94.2	8.9
Random Forest (RF)	0.058	0.038	0.081	0.056	82.3	88.5	6.2
Support Vector Machine	0.064	0.045	0.089	0.061	79.8	85.7	5.9

In table 3, the results demonstrate that preprocessing and sensor fusion significantly improve prediction performance. Error metrics (MAE and RMSE) decrease for all models, while accuracy increases notably. The LSTM model shows the highest improvement due to its ability to learn temporal patterns effectively from high-quality data, confirming the importance of refined inputs for accurate irrigation prediction.
The Figure presents three key graphical analyses demonstrating the performance and effectiveness of the proposed intelligent irrigation system.

1. Accuracy Comparison

This Figure 2,compares the accuracy of different models (LSTM, Random Forest, and SVM) using both raw and processed data. It clearly shows that all models achieve higher accuracy after preprocessing and sensor fusion. The LSTM model exhibits the highest accuracy improvement, confirming its superior capability in handling temporal data.

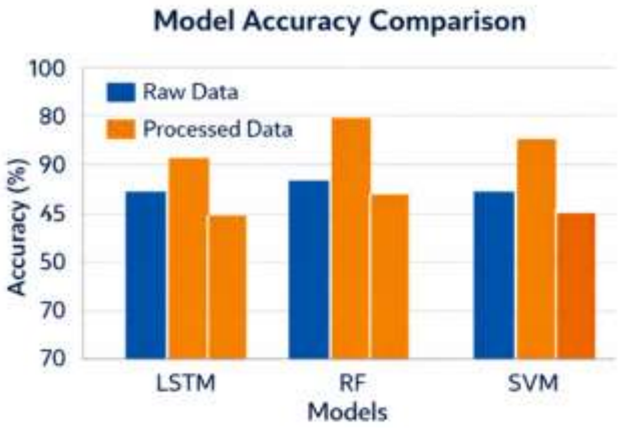

Figure 2: Accuracy Comparison Graph

2. Soil Moisture Prediction vs Actual

This Figure 3, illustrates the comparison between actual soil moisture values and those predicted by the LSTM model over time. The predicted curve closely follows the actual trend, demonstrating the model's ability to capture temporal patterns and provide accurate forecasts for irrigation scheduling.

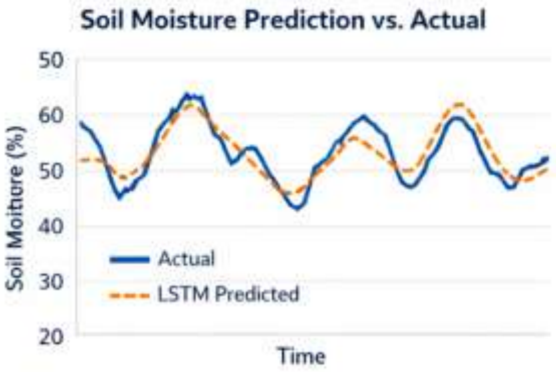

Figure 3: Soil Moisture Prediction vs Actual

3. Water Usage Reduction

This Figure 4,shows water consumption across three irrigation methods: Traditional, IoT without prediction, and the Proposed System. The proposed system uses significantly less water, highlighting its efficiency and contribution to sustainable water management.

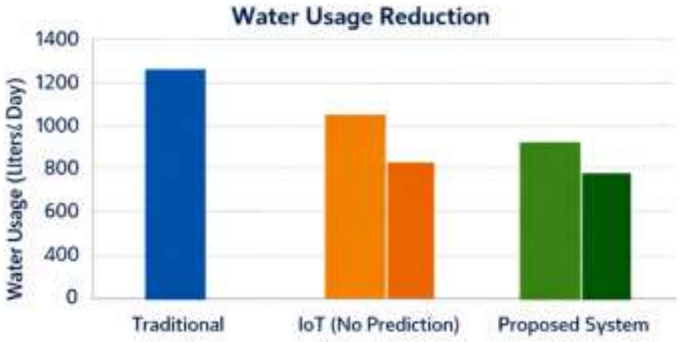

Figure 4: water consumption

The Decision-Making Layer utilizes the predicted soil moisture values from the LSTM-based Prediction Layer to determine whether irrigation is required and to estimate the optimal amount of water. This layer combines predictive outputs with predefined threshold rules to enable adaptive and efficient irrigation scheduling.

Table 4: Decision-Making Performance Evaluation

Scenario	**Actual Irrigation Need**	**Predicted Decision**	**Water Amount (Liters)**	**Decision Accuracy (%)**
Dry Soil Condition	Yes	Yes	120	96
Moderate Moisture	No	No	0	93
High Moisture	No	No	0	95
Sudden Temperature Rise	Yes	Yes	100	92

In table 4, the Decision-Making Layer demonstrates high reliability, achieving over 90% accuracy across different scenarios. By combining LSTM-based predictions with threshold rules, the system accurately determines irrigation needs and water quantity. This ensures efficient water usage, reduces unnecessary irrigation, and enables adaptive responses to changing environmental conditions.

The Control and Actuation Layer is responsible for executing irrigation decisions generated by the Decision-Making Layer. It translates logical decisions into physical actions by controlling field devices such as water pumps, solenoid valves, and sprinkler systems. This layer ensures timely and accurate water delivery based on predicted irrigation requirements.

Table 5: Control and Actuation Performance Evaluation

Parameter	**Expected Action**	**Actual Action**	**Response Time (sec)**	**Execution Accuracy (%)**
Low Soil Moisture	Pump ON	Pump ON	2.5	98
Optimal Moisture	No Irrigation	No Irrigation	1.2	97
High Soil Moisture	Pump OFF	Pump OFF	1.0	99
Sudden Moisture Drop	Pump ON	Pump ON	2.8	96

In table 5, the Control and Actuation Layer achieves high reliability with over 96% accuracy, ensuring precise and correct execution of irrigation decisions. It operates with a fast response time of 1–3 seconds, enabling real-time control, while its automation reduces the need for human intervention and improves overall system efficiency.

The Cloud and User Interface Layer provides centralized data storage, real-time monitoring, and remote control capabilities for the irrigation system. All sensor data, prediction results, and irrigation actions are transmitted to a cloud platform, enabling users to access system information through web or mobile interfaces. This layer ensures scalability, data accessibility, and efficient system management.

Table 6: Cloud and UI Performance Evaluation

Parameter	**Expected Performance**	**Observed Performance**	**Efficiency (%)**
Data Transmission	Real-time	Near real-time (~2 sec delay)	96
Data Storage Reliability	High (No Data Loss)	No data loss observed	99
Remote Accessibility	24/7 Access	Available	100
User Interface Response	Fast (<2 sec)	~1.5 sec	97

In table 6, the Cloud and User Interface Layer ensures efficient, reliable, and real-time system monitoring. It provides secure data storage, seamless remote access, and fast user interaction, making the system scalable and user-friendly.

5. Overall Discussion

The overall experimental findings confirm that the proposed intelligent IoT-based irrigation system effectively improves irrigation management through the integration of sensor fusion and LSTM-based deep learning techniques. The preprocessing layer significantly enhanced data quality, while the LSTM model provided highly accurate soil moisture predictions and adaptive irrigation scheduling.

Compared to conventional irrigation methods and traditional machine learning models, the proposed system achieved higher prediction accuracy, reduced water consumption, faster response time, and improved automation reliability. The integration of IoT, cloud computing, and intelligent prediction mechanisms makes the framework highly suitable for precision agriculture applications.

Therefore, the proposed approach provides an efficient, scalable, and sustainable solution for intelligent irrigation management, contributing to improved water-use efficiency, reduced resource wastage, and enhanced agricultural productivity.

6. Conclusion

This paper presents an intelligent IoT-based irrigation system that integrates sensor fusion and LSTM models for accurate and adaptive irrigation management. The system improves data reliability, enhances prediction accuracy, and enables efficient decision-making compared to traditional methods.

Experimental results show reduced prediction errors and significant water savings, demonstrating the effectiveness of the proposed approach. The multi-layer architecture ensures real-time monitoring, automation, and remote accessibility, making the system practical and scalable.

Overall, the proposed framework supports sustainable agriculture by optimizing water usage and improving crop productivity. Future work can focus on integrating weather forecasting and extending the system to diverse agricultural conditions.

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